



Tailored seasonal climate predictions for wind energy users

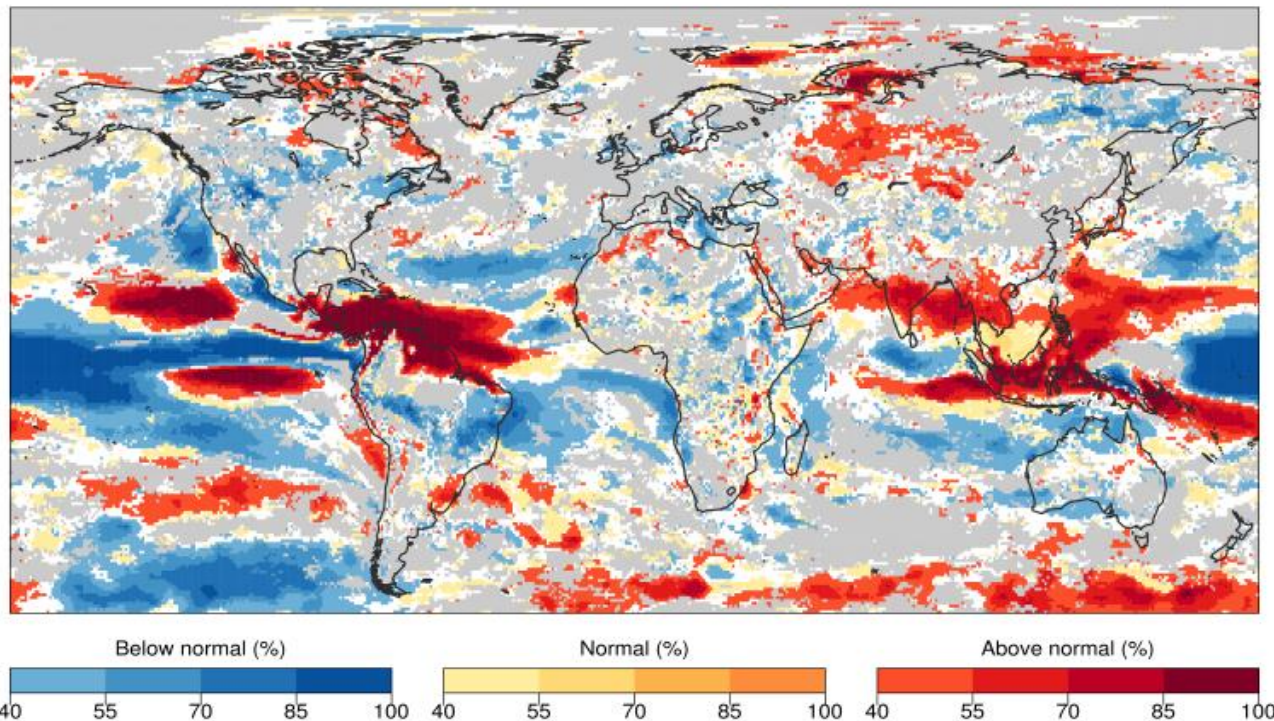
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Nube González-Reviriego and Albert Soret

- From monthly to decadal time scales current energy practices assume that future will be a repetition of the **retrospective climatology**.
- The available seasonal predictions can provide additional value **for wind energy applications**
 - Maintenance works
 - Grid management
 - Financial issues
- Limited application because this information is **untailored** and **hard to** incorporate in a useful manner



Goal: assessment of the forecast quality of the seasonal prediction systems to produce usable information for the wind industry.



ECMWF S4 10-m wind speed seasonal forecast for JJA 2015 initialized the 1st of May. The most likely wind speed category (below-normal, normal or above normal) and its percentage probability to occur is shown. White areas show where the probability is less than 40 % and approximately equal for all three categories. Grey areas show where the climate prediction model doesn't improve the climatology.

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1. Evaluation of different **bias-adjustments** techniques
2. **Forecast quality assessment** of the bias-corrected seasonal predictions
3. Generation of **wind power capacity factor** seasonal predictions

- **Variables:** 10m wind speed and 2m temperature
- **Forecast system:** ECMWF S4 (51-members)
- **Season:** December-January-February (1 lead time)
- **Period :** 1981-2014
- **Reference dataset:** ERA- Interim

As illustration, seasonal predictions in a region in **Canada**, where wind farms are located, has been selected.



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1. Evaluation of different **bias-adjustments techniques**

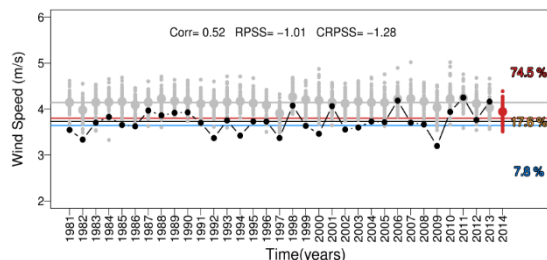
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3. Generation of **wind power capacity factor seasonal predictions**

1. Evaluation of different bias-adjustments



Raw data



Hindcast mean
Bias
Observations mean

Method	Equation	Description	Result
Simple bias correction	$y_{j,i} = (x_{ij} - \bar{x}) \frac{\sigma_{ref}}{\sigma_e} - \bar{o}$	Based on the assumption that both the reference and forecasted distribution are well approximated by a Gaussian distribution.	<p>Corr= 0.51 RPSS= 0.09 CRPSS= 0.11</p> <p>9.8 %</p> <p>72.5 %</p> <p>Time(years)</p>
Calibration method	$y_{j,i} = \alpha x_i + \beta z_{ij}$	Variance inflation modifies the predictions to have the same interannual variance as the reference dataset and corrects the ensemble spread to improve the reliability.	<p>Corr= 0.52 RPSS= 0.09 CRPSS= 0.12</p> <p>9.8 %</p> <p>72.5 %</p> <p>Time(years)</p>
Quantile mapping	$y_{j,i} = (ecdf^{ref})^{-1} ecdf^{mod}(x_{ij})$	It determines for each forecast to which quantile of the forecast climatology it corresponds, and then they are mapped to the corresponding quantile of the observational climatology.	<p>Corr= 0.51 RPSS= 0.11 CRPSS= 0.09</p> <p>5.9 %</p> <p>82.4 %</p> <p>Time(years)</p>

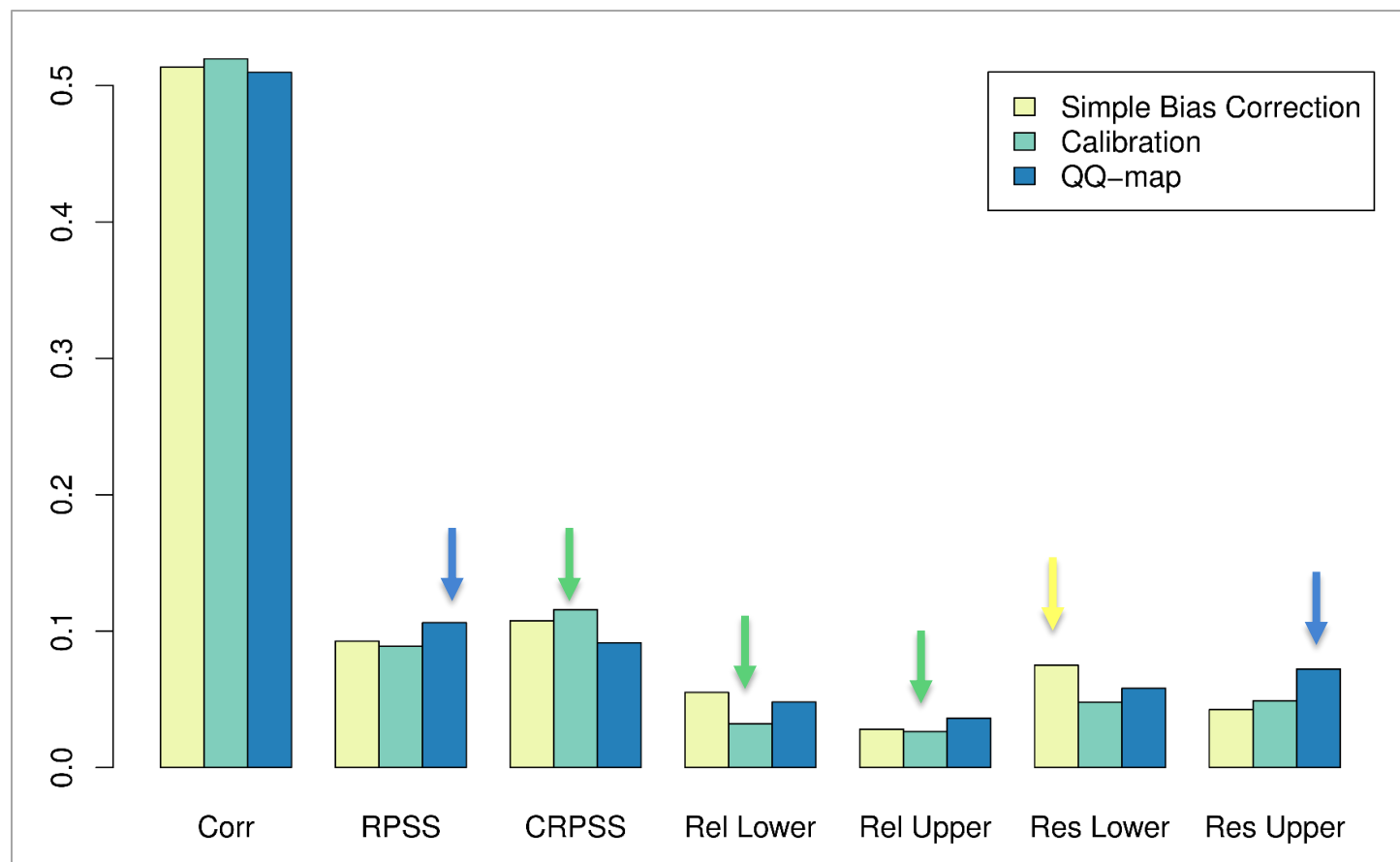
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2. Forecast quality assessment



- Variations between the scores are low for the three different bias-adjustments.
- Calibration method produce the best CRPSS and reliability for the below-normal category and above normal category, however the forecasts corrected with the quantile mapping method produce higher RPSS.

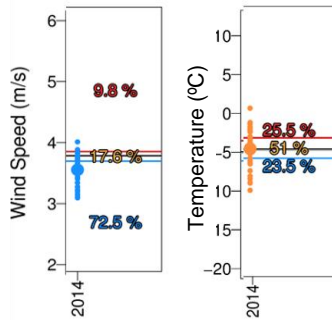
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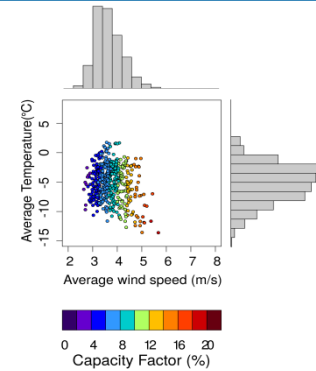
3. Generation of CF seasonal predictions



A) Bias corrected wind speed and temperature



B) CF based on past observations



3. Generation of CF seasonal predictions



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B) CF based on past observations

MacLeod, D., M. Davis, F. J. Doblas-Reyes, (2014). Modelling wind energy generation potential on seasonal timescales with impact surfaces. SPECS Technical Note No.3, 24 pages.

Capacity Factor

$$CF (\%) = \frac{P}{P_{turbine}}$$

Power output curve from Vestas 2 MW

Wind Power:

$$P = \frac{E}{t} = \rho \frac{Av^3}{2} \longrightarrow \boxed{P = \frac{p}{RT} \frac{Av^3}{2}}$$

$$\rho = \frac{p}{RT}$$

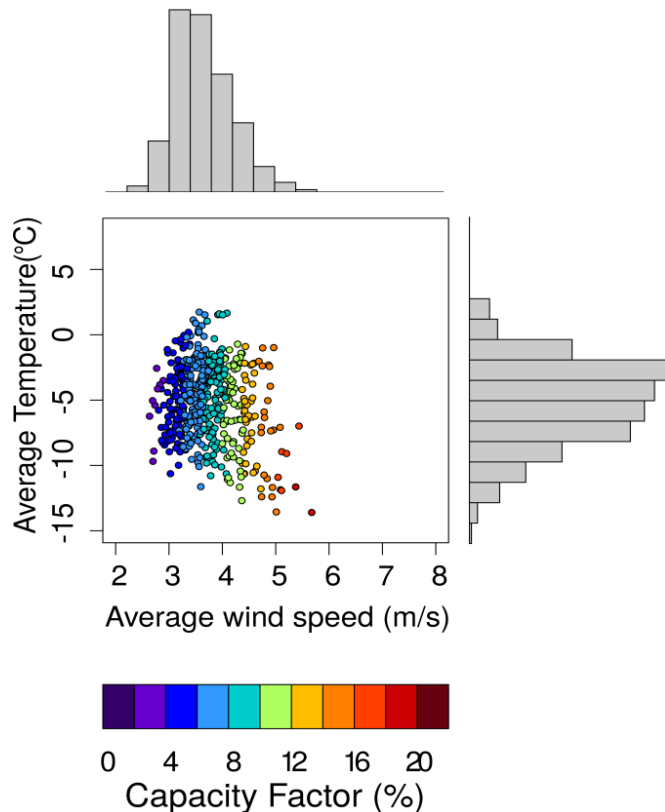
Assumptions

1. Wind profile **power law** is used to extrapolate 10m wind speed to the turbine height

$$\frac{u}{u_r} = \left(\frac{z}{z_r} \right)^{\frac{\alpha}{\alpha + 1}}$$

2. Daily variability in 10-m wind speed and operating limitations of a wind turbine has been modelled by a **Rayleigh distribution** (a simple case of the Weibull distribution with k=2).

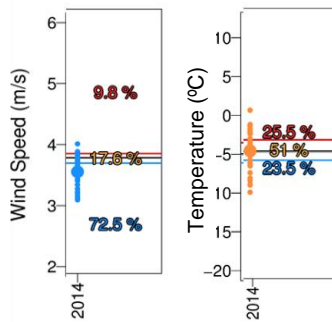
$$f(x) = \frac{x}{S^2} e^{-x^2/2S^2}$$



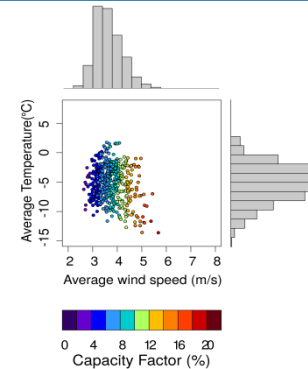
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A) Bias corrected wind speed and temperature



B) CF based on past observations



C) Multivariate linear regression model

$$CF(WS,T) = A WS + B T + C$$

3. Generation of CF seasonal predictions

C) Multivariate linear regression



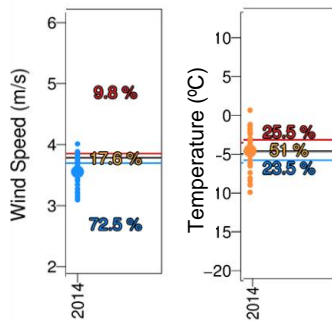
$$CF(WS, T) = A WS + B T + C$$

- Past observations of CF, WS and T are fitted to a multivariate regression and the coefficients **A**, **B** and **C** are obtained.
- Probabilistic **seasonal predictions of WS and T** are fitted to the regression together with the coefficients A, B, C.
- The generated output is the **probabilistic seasonal prediction of the capacity factor**.
- It has been applied in **cross-validation**

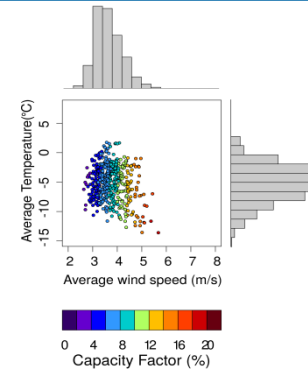
3. Generation of CF seasonal predictions



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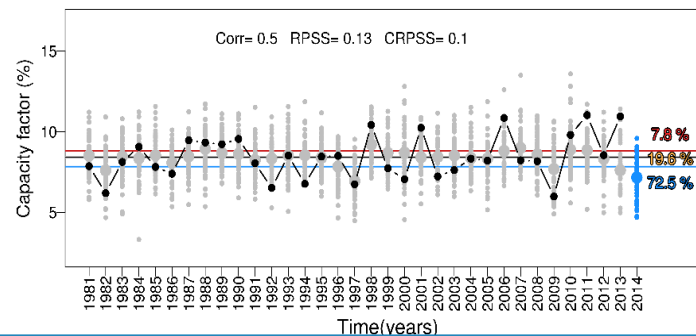
B) CF based on past observations



C) Multivariate linear regression model

$$CF(WS,T) = A WS + B T + C$$

D) Seasonal forecasts of CF

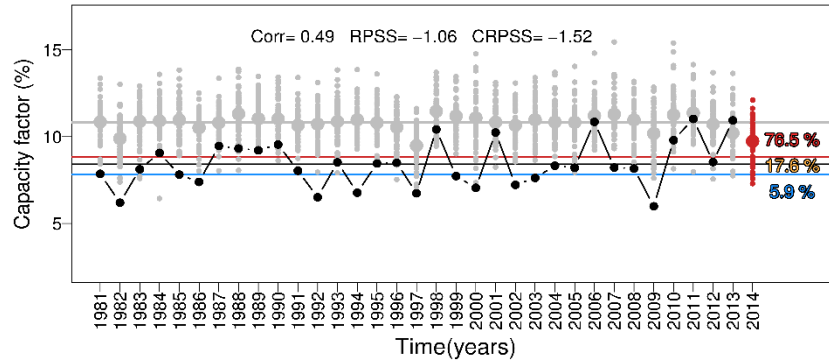


3. Generation of CF seasonal predictions

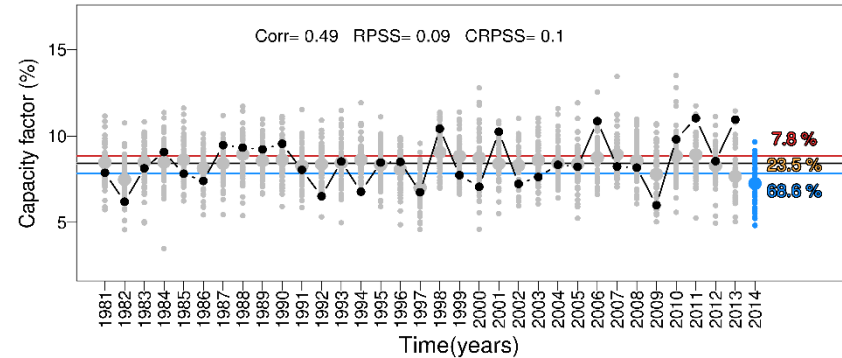


D) Seasonal predictions of CF

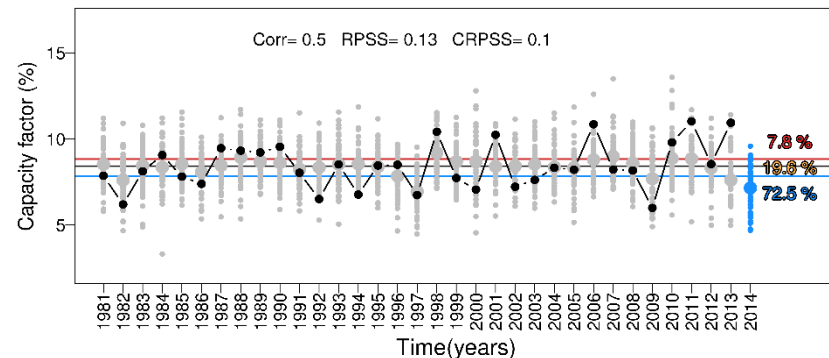
Raw Data



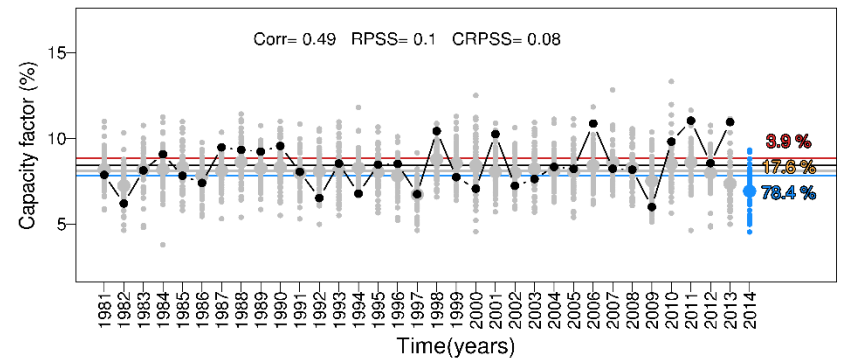
Simple Bias correction



Calibration



Quantile-Quantile mapping



- The transfer model generates bias corrected probabilistic forecasts of capacity factor.
- Seasonal forecasts of capacity factor display positive skill scores which indicates these predictions can add value to the climatology.

Conclusions and prospects

- This study describes a simple methodology to develop **useful information for the wind industry** that can be easily integrated in their decision-making processes.
- Different methods of bias-correction have been used to produce forecasts with **improved forecast quality**.
- The comparison of the three methods indicates that **calibration method displays better reliability** than simple bias correction and quantile mapping.
- Positive skill of CF predictions indicates the **added value** of these forecasts relative to the climatology.
- Future work will focus on the formulation of predictions for specific sites. This is a non-trivial task because the bias-adjustments necessary require long-enough observational references that are not readily available.



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Thank you

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